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客製化產品推薦模式之研究：有限混合與層級貝氏邏輯斯模式之比較

研究成果報告(精簡版)

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計畫主持人：任立中

計畫參與人員：博士班研究生-兼任助理：邵功新

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A Study of Customized Product Recommendation Models: Comparison of Finite Mixture and Hierarchical Bayes Logit Models

ABSCRACT

The purpose of this article is to provide a set of solutions for customized new product recommendation to improve the performance of CRM (Customer Relationship Management) project. We proposed two customized new product recommendation models: finite mixture Probit and hierarchical Bayes Probit model. The proposed methods are tested by random selected customers in a home electronic retailer's CRM database, and results show that the presented customized new product recommendation models perform well. The approach of this paper has its strength to be able to do new product recommendation and cross-selling in database marketing on a one to one basis.

Keyword: Customer Relationship Management; New Product Recommendation; Finite Mixture Probit Model; Hierarchical Bayes Probit Model.

When you have a now product to sell, do you have trouble in identifying the customers who might have higher propensity to buy this product in your CRM (customer relationship management) database? A good new product recommendation system provides high-value of service to customers, enhances cross-selling in database marketing, and generates higher profits for this company. With the CRM database, company now can better understand customer needs, can recommend right product for their customers, and can integrate knowledge into their product design and marketing plans. However, the goal is often difficult to achieve. Nearly half of U.S. implementations and more than 80 percent of European implementations of CRM project are considered failures (Patron 2002). To getting value back out of CRM, a good solution for customized new product recommendation can not be ignored.

Current Solutions for Product Recommendation

Current solutions for product recommendation can be briefly categorized as two types of filtering. The first is collaborative filtering which is based on the similarity between customers' rating. Despite it has been intensively used by internet retailers such as Amazon.com, it still has limitations in practice. In order for collaborative recommendation to be accurate, a large number of transaction data of a given product must be prepared. Accordingly, it is completely limited when new products being encountered.

The other type is content-based filtering which match customer interest profiles with the product attributes. In order for the approach to be effective, sufficiently rich product information as well as personal preference profiles should be available. Accordingly, this approach is limited when new customers are encountered.

Some scholars suggest to using hybrid models to overcome the limitations (Ariely, Lynch and Aparicio 2002; Balabanovic and Shoham 1997; Pazzani 1999). However, the filtering approach still be criticized (Ansari, Essegaier, and Kohli 2000; Iacobucci, Arabie, and Bodapati 2000). First, the proposed filtering techniques are typically based upon customers' ratings data, instead of actual purchases record. This might limits their application in practice. Second, filtering techniques does not base upon statistical method so that they are unable to reflect uncertainty in predictions. To overcome this problem, Ansari, Essegaier, and Kohli (2000) proposed a hierarchical Bayes regression model for internet movie recommendations. The hierarchical Bayes approach can be used to provide recommendations when either new products or new customers are being encountered. Although their study provides great insights, two reasons might challenge the managers' intension to put their idea into CRM practice. First, their study was based upon consumer's preference self-rating data instead of actual transaction records. Can we apply their framework to improve the performance of new product recommendation in CRM project? Second, their study was only focus on one single product category--movie. For most retailers, they sell multi-category products. Accordingly, they are more concern about how to do new product recommendations for mulit-catogory products? The purpose of this article is to provide a solution designed for doing customized new product recommendations. The analytical solution is based upon statistical choice model and derived from our practical experience during the implementation of CRM project of a home electronic appliance retailer.

The outline of this paper is as follows. In the next section, we introduce a CRM case from a home appliance retailer. The steps of proposed solution are illustrated. In the final section, we present the results of estimation and compare the success of hit rates of different methods, and a conclusion was provided in the last section.

A CRM Case form a Home Appliances Retailer

We use the data from the CRM database of a home appliance retailer in Taiwan. They have implemented their CRM system since Jan 01, 1999. Transaction data were available from Jan 01, 1999 to Jan 01 2001. There are 23 products categories selected for analysis including electronic television, VCD, DVD, digital studio, air conditioning, et al. (see figure 1). A random sample of 400 customers was selected for analysis (up to 1153 transaction records). The data of each customer includes their transaction data and demographic information (see table 1).

Figure 1 here

Table 1 (a) here

Table 1 (b) here

Marketing scholars have encouraged the employ of choice model to improve the analytical CRM project (Kamakura et al. 2005). However, there are several challenges for researchers to apply choice model in CRM database. First, lacking of product attributes coding in database. Second, the alternative choices were unavailable because only the real purchased products were recorded in database. Third, methods to integrate data from several kinds of sources were often depended on researchers' expertise as well as experience. In the following section, we develop a system way of analytical solution designed to overcome these challenges and to improve the performance of new product recommendation in CRM practice.

The Procedures and Logic for Proposed Models

The underlying assumption of proposed models is the features of these products can be identified into common attributes. For instance, the common attributes for consumer electronic products are country of origin, product design, function, price level, et al. In that case, the procedures and logic for the proposed model are as follows: (1) we have access to a retailer' customer database that consists customers' transaction records of multi-category products and demographic information; (2) in each transaction, customer chooses one product from a series of potential choice set; (3) the common attributes of products can be identified and coded; (4) individual's preference toward each particular attribute are estimated; (5) the utilities of each alternative products are predicted in order to recommend new products to customers.

In order to test the ability to recommend new products, we separate customers' transaction records into two groups: in sample and holdout sample. The hold out sample is the last one purchase record of each customer. The others transaction records of each customer were used as in sample records to estimate parameters. Our method follows the steps: coding of product attribute, developing pseudo choice set, statistical modeling, estimation, and utilities prediction.

Coding of Product Attributes

From an information cue theoretic perspective, products may be conceived as consisting of an array of information cues, such as design, brand name, price, and country of origin (Bilkey and Nes 1982). Each cue provides customers with a basis for evaluating the product, which might influence customers' purchase decision. In order to decompose customers' preference toward these attributes, we collect and integrate data from three kinds of sources: product managers' opinions, CRM database and magazine. Product attributes coding includes five categories. They are specified as follows: (1) Country of origin (country of manufacturing & country of brand): US, Japan, Taiwan, China & East and South Asia countries, and the other countries. (2) Functioning: superiority, middle level and weak in function. (3) Product design: good or not good in design. (4) Price ratio: a continuous variable, which is calculated form the database by comparing the price of purchased product and the average prices in same product category for a given time period closed to the transaction date. (5) word-of-mouth: good or not in word-of-mouth. Data was collected form a magazine in which there is an annual survey regarding consumers' favorite brands in each product categories in year 2000.

Pseudo Choice Set

In order to simulate the available choices faced by consumers when they made their purchase decision in retailer store, we create pseudo choice set. In this step, we includes and integrated the other customers' transaction records form 90 days earlier than and 30 days later than the actual purchase record of the target product made by the customer. The mean of pseudo choice set is 10.83, and the standard deviation is 5.28.

Model

To compare the performance of hit rates of different methods, we provide two basic solutions for comparison: random recommendation and Probit model. The others are two types of customized new product recommendation models: Finite Mixture Probit Model and hierarchical Bayesian Probit model. In a finite mixture Probit model, the individual preferences of a given customer can be obtained by the weighted combination of probability and preference form similar customers. In a hierarchical Bayesian Probit model, a specific attribute weight for each individual can be estimated by pooling of information form both individual and across populations. Details of model specifications are stated in appendix.

Results

Table 2 is the results of parameters estimated from Probit model, finite mixture Probit model, and hierarchical Bayes Probit model. Some variable of country origin (i.e., country of brand and country of manufacturing) were deleted due to either multicollinearity or too few cases that might ruin the results of estimations. In the Probit model, we can see that consumers have positive preference toward made in US. However, consumers have negative attitude toward either country of brand in Japan or US. Comparing with middle level in function, consumers have higher preference in either superiority or weak in functioning. Besides, they have positive preference toward good design and word-of-mouth and negative preference toward price ratio. The table 2 also shows the estimated preference parameters of three finite mixture latent classes. In the first segment, consumers have positive preference toward good design, price ratio and word-of-mouth. People in this segment prefer good design and word-on-mouth products. They are more willing to pay for relative higher price. People in the second segment are price consciousness; they have negative preference toward price ratio and word-of-mouth. Finally, people in the third segment are value consciousness; they have positive preference toward function and word-of-mouth but negative preference toward price ratio. The last two columns in table 2 are the results of hierarchical Bayes Probit model. The parameters were the posterior mean and posterior standard deviation of individual beta parameters. The posterior standard deviation of beta can represents the heterogeneity in consumers' preference structure rather than represents the standard error in beta estimation. In hierarchical Bayes Probit model, the individual's demographic or behavior information can be included to predict individualized parameters. Table 3 shows the results of these Γ coefficients estimated form hierarchical Bayes Probit model. For example, compared with customers age below 20, customers age above 60 have negative preference toward price ratio.

Table 2 here

Table 3 here

After obtaining the estimated beta coefficients, we predict the utilities for each product in pseudo choice set. Then, the set of utilities in each pseudo choice set were ranked form high to low. The ranked number of actual purchased record can be used to represent the numbers of recommended products that is required in order to hit the target product in each choice set. As shows in table 4, the results were aggregated to test the predictive power of different methods. In the in sample hit rates, the hierarchical Bayes Probit model out perform finite mixture Probit model, and they both out perform Probit model and random recommendation. With regard to the hold out sample hit rates, the hit rates among the first three recommendations of finite mixture Probit model is quite close to hierarchical Bayes Probit model. The hierarchical Bayes Probit model still out performs the other models.

Table 4 here

Conclusion

The purpose of this article is to provide a solution designed for new product recommendation. We propose two customized new product recommendation methods. Both methods can help us to decompose consumers' preference toward particular attribute, and then help us to predict the purchase probabilities. The results of hit rates comparison show that both of our proposed customized new product recommendation models perform well in either in sample or hold out sample prediction. Thus, we suggest managers can apply these customized new product recommendations when they want to improved their performance in new product recommendation.

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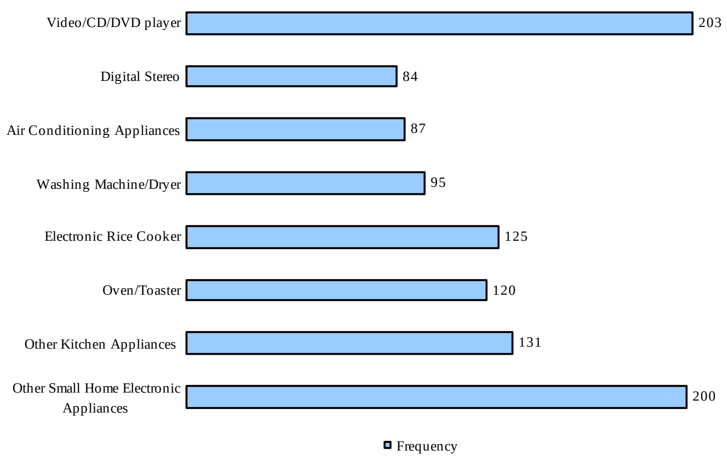

Figure 1 is the observed frequencies of each product categories.

ember ID	Purchase Amount	Quantity	Purchase date	Category Code	Store ID	Brand	Product	Model
20009425	8500	1	19990704	12502	1	RCA	20 inches TV	F21634TW
20009425	680	1	19990916	1303	1	ALIGN	Oven	OCE-8037
20009425	1980	1	20000729	1204	2	AIWA	Digital Stereo	XRAKH300
20012511	9500	1	20000816	22101	3	TECO	Refrigerator	RE-1601S
20015739	18000	1	20001027	22302	4	TECO	Refrigerator	RE6001N
20015739	13500	1	20001027	23103	11	SAMPO	Washing machine	ES-103SBF
20016493	19000	1	19991121	10401	8	AIWA	Digital Stereo	XRAKH100
20016493	2490	1	20000618	2101	7	HITACHI	Vacuum Cleaner	PV-C25
20016493	690	1	20000824	3301	7	PUMP	Electric Iron	TSK-750CS
20020521	1690	1	20000104	25101	10	SANYO	DVD Player	R-CF01T
……..	……..	……..	……..	……..	……	……..	……..	……..
20940532	2988	1	20000131	10401	14	SANYO	Digital Stereo	DC-LU6

Table 1(a) is an example of data available in CRM transaction database.

Member ID	Card Starting Date	Gender	Age	Post No.
20009425	10/14/2000	1	32	557
20012511	07/07/1997	1	38	820
20015739	11/18/2000	1	40	557
20016493	12/10/2000	1	27	241
20019338	09/16/1999	1	30	330
20002102	01/27/1990	2	31	830
20002383	07/28/2000	1	34	812
20013243	06/24/1994	2	64	704
20013421	01/24/1992	1	84	802
20015621	10/28/2000	1	32	356
……..	……..	……..	……..	……..
20020532	08/09/1999	2	42	360

Table 1(b) is an example of data stored in CRM customer information database.

	Probit Model		Finite Mixture Probit Model						Hierarchical Bayes Probit Model	
			Segment 1		Segment 2		Segment 3			
	Beta Coefficient	Standard Error	Beta Coefficient	Standard Error	Beta Coefficient	Standard Error	Beta Coefficient	Standard Error	Posterior Mean of Beta	Posterior Standard Deviation of Beta
Constant	- 1.47***	0.07	- 2.56***	0.48	- 0.54	1.27	- 1.12	0.13	- 1.31	1.54
Made in China	- 0.06	0.05	- 0.07	0.25	- 0.01	0.61	- 0.08	0.09	- 0.11	0.44
Made in Japan	- 0.10	0.08	- 0.15	0.47	- 1.17	1.33	- 0.15	0.14	- 0.19	0.55
Made in US	0.29***	0.12	0.31	0.49	- 0.20	3.09	0.18	0.18	- 0.03	0.98
Brand in Japan	- 0.16***	0.06	- 0.10	0.34	0.57	0.80	- 0.15*	0.09	- 0.15	0.42
Brand in US	- 0.32***	0.09	- 0.44	0.34	- 0.18	1.07	- 0.25*	0.14	- 0.53	1.10
Superiority in Function	0.18***	0.07	0.12	0.31	1.21	0.79	0.16*	0.09	0.20	0.47
Weak in Function	0.16***	0.06	- 0.12	0.24	0.94	1.19	0.21***	0.08	0.18	0.39
Good Design	0.17***	0.05	0.45***	0.18	0.33	0.63	0.03	0.07	0.13	0.40
Price Ratio	- 0.15***	0.05	0.80***	0.25	- 1.62*	1.11	- 0.51***	0.11	- 0.47	0.90
Word-of- Mouth	0.44***	0.04	0.36*	0.23	- 1.62*	0.93	0.60***	0.07	0.48	0.71

In sample is an unbalance panel that includes 400 individuals. The total number of observations is 8481
p* < .1, ** *p* < .05, * *p* < .01
Made in Japan means product manufactured in Japan
COO in Japan means the country of origin of brand is Japan

Table 2: This table shows the results of parameters estimated from Probit model, finite mixture Probit model, and hierarchical Bayes Probit model.

		Constant	Made in China	Made in Japan	Made in US	COO in Japan	COO in US	Superiority in Function	Weak in Function	Superiority in Design	Price Ratio	Word-of-Mouth
Constant	Posterior Mean	4.72 ***	- 2.10 ***	- 2.05 ***	- 2.89 ***	0.26	- 2.65 ***	1.25	1.45 **	- 1.94 ***	- 4.27 ***	0.28
	Posterior STD	(1.18)	(0.87)	(0.91)	(1.08)	(0.89)	(1.03)	(0.88)	(0.83)	(0.85)	(0.96)	(0.80)
Gender	Posterior Mean	0.02	- 0.26	0.03	0.59	- 0.08	- 0.17	- 0.29	- 0.02	0.10	0.12	0.07
	Posterior STD	(0.46)	(0.32)	(0.48)	(0.63)	(0.39)	(0.43)	(0.38)	(0.34)	(0.36)	(0.44)	(0.34)
Age 21-30	Posterior Mean	- 0.55	0.85	1.42 ***	3.24 ***	- 0.95	0.04	- 0.59	- 0.18	0.93	- 0.12	- 0.71
	Posterior STD	(0.86)	(0.69)	(0.68)	(0.73)	(0.95)	(1.14)	(0.67)	(0.68)	(0.60)	(0.73)	(0.67)
Age 31-40	Posterior Mean	- 0.96	1.00	1.67 ***	2.76 ***	- 1.00	1.75 **	- 0.59	- 0.20	0.74	0.03	- 0.08
	Posterior STD	(0.79)	(0.70)	(0.79)	(0.80)	(0.83)	(1.01)	(0.59)	(0.61)	(0.54)	(0.74)	(0.59)
Age 41-50	Posterior Mean	- 0.95	1.27 **	1.67 ***	1.72 ***	- 0.89	2.12 ***	- 0.28	0.10	0.67	- 0.24	- 0.29
	Posterior STD	(0.78)	(0.68)	(0.66)	(0.77)	(0.89)	(0.96)	(0.60)	(0.59)	(0.58)	(0.72)	(0.58)
Age 51-60	Posterior Mean	- 1.00	1.00	1.81 ***	2.20 ***	- 0.93	2.06 ***	- 0.81	- 0.16	0.81	- 0.10	0.26
	Posterior STD	(0.84)	(0.70)	(0.75)	(0.79)	(0.85)	(0.99)	(0.64)	(0.62)	(0.56)	(0.73)	(0.58)
Age above 60	Posterior Mean	- 0.59	1.40 ***	1.02	1.59	- 0.15	2.59 ***	0.01	0.12	0.26	- 1.16 **	0.53
	Posterior STD	(0.93)	(0.62)	(0.92)	(0.90)	(0.96)	(1.04)	(0.72)	(0.73)	(0.66)	(0.67)	(0.69)
Frequency	Posterior Mean	- 0.03	0.00	0.02	0.02	- 0.02	0.01	0.00	0.01	0.01	0.01	- 0.01
	Posterior STD	(0.10)	(0.09)	(0.12)	(0.14)	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)	(0.09)	(0.08)
Log_Amount	Posterior Mean	- 0.59 *	0.13	0.01	0.02	0.08	0.04	- 0.04	- 0.15	0.14	0.45	0.04
	Posterior STD	(0.36)	(0.27)	(0.30)	(0.32)	(0.25)	(0.29)	(0.28)	(0.26)	(0.26)	(0.30)	(0.25)

*p < .1, ** p < .05, *** p < .01
Log_amount means log average purchase amount

Table 3: This table shows the posterior mean and posterior standard deviation of Γ coefficients

	In Sample Hit Rates (cumulative percentage)				Out Sample Hit Rates (cumulative percentage)			
Number of Product Recommended	(1) Random Recommendation	(2) Probit Model	(3) Finite mixture Probit Model	(4) Hierarchical Bayes Probit	(1) Random Recommendation	(2) Probit Model	(3) Finite mixture Probit Model	(4) Hierarchical Bayes Probit
1	0.1128 %	0.2229 %	0.3325 %	0.4187 %	0.1207 %	0.2076 %	0.2398 %	0.2632 %
2	0.2242 %	0.3756 %	0.5406 %	0.6392 %	0.2414 %	0.3743 %	0.4561 %	0.4415 %
3	0.3371 %	0.5000 %	0.6761 %	0.7783 %	0.3621 %	0.5029 %	0.5819 %	0.5731 %
4	0.4472 %	0.6108 %	0.7685 %	0.8719 %	0.4828 %	0.6287 %	0.6754 %	0.7076 %
5	0.5553 %	0.7131 %	0.8349 %	0.9187 %	0.6013 %	0.7368 %	0.7661 %	0.8216 %
6	0.6527 %	0.7956 %	0.8805 %	0.9421 %	0.6993 %	0.8187 %	0.8509 %	0.8977 %
7	0.7304 %	0.8461 %	0.9089 %	0.9631 %	0.7710 %	0.8626 %	0.8918 %	0.9328 %
8	0.7902 %	0.8830 %	0.9335 %	0.9791 %	0.8194 %	0.8977 %	0.9240 %	0.9678 %
9	0.8369 %	0.9076 %	0.9483 %	0.9852 %	0.8772 %	0.9240 %	0.9591 %	0.9883 %
10	0.8695 %	0.9409 %	0.9557 %	0.9902 %	0.8793 %	0.9415 %	0.9678 %	0.9942 %

A random sample of 400 customers' transactions was selected for analysis. The last one purchase records of sampled customers were selected as hold out sample. There are 58 customer samples with only one transaction record. Accordingly, the hold out sample contains 342 actual transaction records of 342 customers. The in sample contains 811 actual transaction records of 400 customers

Table 4 is the comparison of cumulative percentage of hit rates. The hierarchical Bayes Probit model out performs the other models in either in sample and hold out sample prediction.

Appendix

To compare the performance of hit rates, we provide two basic solutions and two customized new product recommendation model for comparison.

Random Recommendation

The first one is random recommendation. It is assumed that no information regarding customer' preferences is available. If there are 10 products for choice, the hit rate for randomly recommending one product is 1/10.

Probit model

It is assumed no knowledge regarding individual's preference. However, the knowledge regarding the preference structure of aggregate market is available. Thus, their new product recommendations are based upon the same preference structure of their customers rather then customized new product recommendation. The Probit model is specified as follows:

$$y_{ij} = x'_{ij}\beta_i + \varepsilon_{ij} \qquad y_{ij} = 0,1, \quad i = 1,2,...,n, \quad j = 1,2,..., J_i$$

where ε_{ijm} follow normal distribution. Let y_{ij} to denote the choice made by individual *i in* J_i choice occasions, and *x* is a set of common product attributes.

Finite Mixture Probit Model

A finite mixture model that employs a finite set of mass points to capture heterogeneity has a history for the analysis of individual heterogeneity. It is assumed that individuals are implicitly sorted into a set of S classes, s=1, 2,…..S. In marketing application, these classes can be regarded as customer segments in the market. The following is a finite mixture Probit model for choice made by individual i (i=1, 2,…., N) observed in J_i choice situations, where x is a set of common product attributes. Let y_{ij} to denote the specific choice made by individual i in choice situation J_i, so that the model provides

$$\text{Prob}(y_{ij} = 1 \mid \text{class} = s) = \frac{\exp(\mathrm{x_{ij}}'\beta_s)}{1 + \exp(\mathrm{x_{ij}}'\beta_s)}$$

The individual specific parameter vector is $\hat{\beta}_i = \sum_{s=1}^{S} \hat{H}_{s|i} \hat{\beta}_s$ (Kamakura and Russell 1989). $\hat{H}_{s|i}$ is the individual i 's probabilities of being class s. This formula will be used to estimate individual preference toward product attributes to help us to predictive the purchase probability of any selected new or existing products.

Hierarchical Bayes Probit Model

The hierarchical Bayes approaches to modeling consumer heterogeneity have been conducted over a wide range of marketing problems (e.g., Allenby and Ginter 1995; Allenby, Arora, and Ginter 1998; Rossi and Allenby 2003). The model we will employ is the hierarchical Bayes Probit model. Let y_{ij} to denote the specific choice made by individual i in choice situation J_i,, x is a set of common product attributes,

$$y_{ij} = x'_{ij}\,\beta_i + \varepsilon_{ij} \qquad y_{ij} = 0,1, \quad i = 1, 2, ..., n, \quad j = 1, 2, ..., J_i$$

$$\beta_i = \Gamma \mathrm{z}_i + \zeta_i$$

where ε_{ij} follow normal distribution, n subjects or customers, and J_i choice occasions of subject *i*. β_i is a matrix of individualized preference coefficients, and Γ is a matrix of coefficients that relate β_i to the value of z_i, and z_i is a vector of covariates that account for observed heterogeneity. In this study, the covariate includes demographic variables (i.e., age, gender) and observed behavior variables in database (log average purchase amount and frequency). ζ_i is unobserved heterogeneity component, which is assumed to be multivariate normal distribution (Allenby and Ginter 1995). β_i will be used in this study to estimate individual preference toward product attributes to help us to predictive the purchase probability of any new products.

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Customized New Product Recommendation in CRM Database

ABSCRACT

The purpose of this article is to provide a set of solutions for customized new product recommendation to improve the performance of CRM (Customer Relationship Management) project. We proposed two customized new product recommendation models: finite mixture Probit and hierarchical Bayes Probit model. The proposed methods are tested by random selected customers in a home electronic retailer's CRM database, and results show that the presented customized new product recommendation models perform well. The approach of this paper has its strength to be able to do new product recommendation and cross-selling in database marketing on a one to one basis.

Keyword: Customer Relationship Management; New Product Recommendation; Finite Mixture Probit Model; Hierarchical Bayes Probit Model.

When you have a now product to sell, do you have trouble in identifying the customers who might have higher propensity to buy this product in your CRM (customer relationship management) database? A good new product recommendation system provides high-value of service to customers, enhances cross-selling in database marketing, and generates higher profits for this company. With the CRM database, company now can better understand customer needs, can recommend right product for their customers, and can integrate knowledge into their product design and marketing plans. However, the goal is often difficult to achieve. Nearly half of U.S. implementations and more than 80 percent of European implementations of CRM project are considered failures (Patron 2002). To getting value back out of CRM, a good solution for customized new product recommendation can not be ignored.

Current Solutions for Product Recommendation

Current solutions for product recommendation can be briefly categorized as two types of filtering. The first is collaborative filtering which is based on the similarity between customers' rating. Despite it has been intensively used by internet retailers such as Amazon.com, it still has limitations in practice. In order for collaborative recommendation to be accurate, a large number of transaction data of a given product must be prepared. Accordingly, it is completely limited when new products being encountered. The other type is content-based filtering which match customer interest profiles with the product attributes. In order for the approach to be effective, sufficiently rich product information as well as personal preference profiles should be available. Accordingly, this approach is limited when new customers are encountered.

Some scholars suggest to using hybrid models to overcome the limitations (Ariely, Lynch and Aparicio 2002; Balabanovic and Shoham 1997; Pazzani 1999). However, the filtering approach still be criticized (Ansari, Essegaier, and Kohli 2000; Iacobucci, Arabie, and Bodapati 2000). First, the proposed filtering techniques are typically based upon customers' ratings data, instead of actual purchases record. This might limits their application in practice. Second, filtering techniques does not base upon statistical method so that they are unable to reflect uncertainty in predictions. To overcome this problem, Ansari, Essegaier, and Kohli (2000) proposed a hierarchical Bayes regression model for internet movie recommendations. The hierarchical Bayes approach can be used to provide recommendations when either new products or new customers are being encountered. Although their study provides great insights, two reasons might challenge the managers' intension to put their idea into CRM practice. First, their study was based upon consumer's preference self-rating data instead of actual transaction records. Can we apply their framework to improve the performance of new product recommendation in CRM project? Second, their study was only focus on one single product category--movie. For most retailers, they sell multi-category products. Accordingly, they are more concern about how to do new product recommendations for mulit-catogory products? The purpose of this article is to provide a solution designed for doing customized new product recommendations. The analytical solution is based upon statistical choice model and derived from our practical experience during the implementation of CRM project of a home electronic appliance retailer.

The outline of this paper is as follows. In the next section, we introduce a CRM case from a home appliance retailer. The steps of proposed solution are illustrated. In the final section, we present the results of estimation and compare the success of hit rates of different methods, and a conclusion was provided in the last section.

A CRM Case form a Home Appliances Retailer

We use the data from the CRM database of a home appliance retailer in Taiwan. They have implemented their CRM system since Jan 01, 1999. Transaction data were available from Jan 01, 1999 to Jan 01 2001. There are 23 products categories selected for analysis including electronic television, VCD, DVD, digital studio, air conditioning, et al. (see figure 1). A random sample of 400 customers was selected for analysis (up to 1153 transaction records). The data of each customer includes their transaction data and demographic information (see table 1).

Figure 1 here

Table 1 (a) here

Table 1 (b) here

Marketing scholars have encouraged the employ of choice model to improve the analytical CRM project (Kamakura et al. 2005). However, there are several challenges for researchers to apply choice model in CRM database. First, lacking of product attributes coding in database. Second, the alternative choices were unavailable because only the real purchased products were recorded in database. Third, methods to integrate data from several kinds of sources were often depended on researchers' expertise as well as experience. In the following section, we develop a system way of analytical solution designed to overcome these challenges and to improve the performance of new product recommendation in CRM practice.

The Procedures and Logic for Proposed Models

The underlying assumption of proposed models is the features of these products can be identified into common attributes. For instance, the common attributes for consumer electronic products are country of origin, product design, function, price level, et al. In that case, the procedures and logic for the proposed model are as follows: (1) we have access to a retailer' customer database that consists customers' transaction records of multi-category products and demographic information; (2) in each transaction, customer chooses one product from a series of potential choice set; (3) the common attributes of products can be identified and coded; (4) individual's preference toward each particular attribute are estimated; (5) the utilities of each alternative products are predicted in order to recommend new products to customers.

In order to test the ability to recommend new products, we separate customers' transaction records into two groups: in sample and holdout sample. The hold out sample is the last one purchase record of each customer. The others transaction records of each customer were used as in sample records to estimate parameters. Our method follows the steps: coding of product attribute, developing pseudo choice set, statistical modeling, estimation, and utilities prediction.

Coding of Product Attributes

From an information cue theoretic perspective, products may be conceived as consisting of an array of information cues, such as design, brand name, price, and country of origin (Bilkey and Nes 1982). Each cue provides customers with a basis for evaluating the product, which might influence customers' purchase decision. In order to decompose customers' preference toward these attributes, we collect and integrate data from three kinds of sources: product managers' opinions, CRM database and magazine. Product attributes coding includes five categories. They are specified as follows: (1) Country of origin (country of manufacturing & country of brand): US, Japan, Taiwan, China & East and South Asia countries, and the other countries. (2) Functioning: superiority, middle level and weak in function. (3) Product design: good or not good in design. (4) Price ratio: a continuous variable, which is calculated form the database by comparing the price of purchased product and the average prices in same product category for a given time period closed to the transaction date. (5) word-of-mouth: good or not in word-of-mouth. Data was collected form a magazine in which there is an annual survey regarding consumers' favorite brands in each product categories in year 2000.

Pseudo Choice Set

In order to simulate the available choices faced by consumers when they made their purchase decision in retailer store, we create pseudo choice set. In this step, we includes and integrated the other customers' transaction records form 90 days earlier than and 30 days later than the actual purchase record of the target product made by the customer. The mean of pseudo choice set is 10.83, and the standard deviation is 5.28.

Model

To compare the performance of hit rates of different methods, we provide two basic solutions for comparison: random recommendation and Probit model. The others are two types of customized new product recommendation models: Finite Mixture Probit Model and hierarchical Bayesian Probit model. In a finite mixture Probit model, the individual preferences of a given customer can be obtained by the weighted combination of probability and preference form similar customers. In a hierarchical Bayesian Probit model, a specific attribute weight for each individual can be estimated by pooling of information form both individual and across populations. Details of model specifications are stated in appendix.

Results

Table 2 is the results of parameters estimated from Probit model, finite mixture Probit model, and hierarchical Bayes Probit model. Some variable of country origin (i.e., country of brand and country of manufacturing) were deleted due to either multicollinearity or too few cases that might ruin the results of estimations. In the Probit model, we can see that consumers have positive preference toward made in US. However, consumers have negative attitude toward either country of brand in Japan or US. Comparing with middle level in function, consumers have higher preference in either superiority or weak in functioning. Besides, they have positive preference toward good design and word-of-mouth and negative preference toward price ratio. The table 2 also shows the estimated preference parameters of three finite mixture latent classes. In the first segment, consumers have positive preference toward good design, price ratio and word-of-mouth. People in this segment prefer good design and word-on-mouth products. They are more willing to pay for relative higher price. People in the second segment are price consciousness; they have negative preference toward price ratio and word-of-mouth. Finally, people in the third segment are value consciousness; they have positive preference toward function and word-of-mouth but negative preference toward price ratio. The last two columns in table 2 are the results of hierarchical Bayes Probit model. The parameters were the posterior mean and posterior standard deviation of individual beta parameters. The posterior standard deviation of beta can represents the heterogeneity in consumers' preference structure rather than represents the standard error in beta estimation. In hierarchical Bayes Probit model, the individual's demographic or behavior information can be included to predict individualized parameters. Table 3 shows the results of these Γ coefficients estimated form hierarchical Bayes Probit model. For example, compared with customers age below 20, customers age above 60 have negative preference toward price ratio.

Table 2 here

Table 3 here

After obtaining the estimated beta coefficients, we predict the utilities for each product in pseudo choice set. Then, the set of utilities in each pseudo choice set were ranked form high to low. The ranked number of actual purchased record can be used to represent the numbers of recommended products that is required in order to hit the target product in each choice set. As shows in table 4, the results were aggregated to test the predictive power of different methods. In the in sample hit rates, the hierarchical Bayes Probit model out perform finite mixture Probit model, and they both out perform Probit model and random recommendation. With regard to the hold out sample hit rates, the hit rates among the first three recommendations of finite mixture Probit model is quite close to hierarchical Bayes

Probit model. The hierarchical Bayes Probit model still out performs the other models.

Table 4 here

Conclusion

The purpose of this article is to provide a solution designed for new product recommendation. We propose two customized new product recommendation methods. Both methods can help us to decompose consumers' preference toward particular attribute, and then help us to predict the purchase probabilities. The results of hit rates comparison show that both of our proposed customized new product recommendation models perform well in either in sample or hold out sample prediction. Thus, we suggest managers can apply these customized new product recommendations when they want to improved their performance in new product recommendation.

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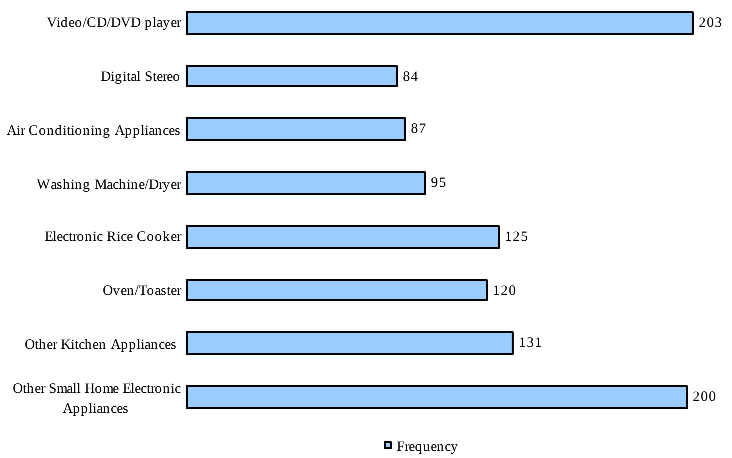

Figure 1 is the observed frequencies of each product categories.

ember ID	Purchase Amount	Quantity	Purchase date	Category Code	Store ID	Brand	Product	Model
20009425	8500	1	19990704	12502	1	RCA	20 inches TV	F21634TW
20009425	680	1	19990916	1303	1	ALIGN	Oven	OCE-8037
20009425	1980	1	20000729	1204	2	AIWA	Digital Stereo	XRAKH300
20012511	9500	1	20000816	22101	3	TECO	Refrigerator	RE-1601S
20015739	18000	1	20001027	22302	4	TECO	Refrigerator	RE6001N
20015739	13500	1	20001027	23103	11	SAMPO	Washing machine	ES-103SBF
20016493	19000	1	19991121	10401	8	AIWA	Digital Stereo	XRAKH100
20016493	2490	1	20000618	2101	7	HITACHI	Vacuum Cleaner	PV-C25
20016493	690	1	20000824	3301	7	PUMP	Electric Iron	TSK-750CS
20020521	1690	1	20000104	25101	10	SANYO	DVD Player	R-CF01T
……..	……..	……..	……..	……..	……	……..	……..	……..
20940532	2988	1	20000131	10401	14	SANYO	Digital Stereo	DC-LU6

Table 1(a) is an example of data available in CRM transaction database.

Member ID	Card Starting Date	Gender	Age	Post No.
20009425	10/14/2000	1	32	557
20012511	07/07/1997	1	38	820
20015739	11/18/2000	1	40	557
20016493	12/10/2000	1	27	241
20019338	09/16/1999	1	30	330
20002102	01/27/1990	2	31	830
20002383	07/28/2000	1	34	812
20013243	06/24/1994	2	64	704
20013421	01/24/1992	1	84	802
20015621	10/28/2000	1	32	356
……..	……..	……..	……..	……..
20020532	08/09/1999	2	42	360

Table 1(b) is an example of data stored in CRM customer information database.

	Probit Model		Finite Mixture Probit Model						Hierarchical Bayes Probit Model	
			Segment 1		Segment 2		Segment 3			
	Beta Coefficient	Standard Error	Beta Coefficient	Standard Error	Beta Coefficient	Standard Error	Beta Coefficient	Standard Error	Posterior Mean of Beta	Posterior Standard Deviation of Beta
Constant	- 1.47***	0.07	- 2.56***	0.48	- 0.54	1.27	- 1.12	0.13	- 1.31	1.54
Made in China	- 0.06	0.05	- 0.07	0.25	- 0.01	0.61	- 0.08	0.09	- 0.11	0.44
Made in Japan	- 0.10	0.08	- 0.15	0.47	- 1.17	1.33	- 0.15	0.14	- 0.19	0.55
Made in US	0.29***	0.12	0.31	0.49	- 0.20	3.09	0.18	0.18	- 0.03	0.98
Brand in Japan	- 0.16***	0.06	- 0.10	0.34	0.57	0.80	- 0.15*	0.09	- 0.15	0.42
Brand in US	- 0.32***	0.09	- 0.44	0.34	- 0.18	1.07	- 0.25*	0.14	- 0.53	1.10
Superiority in Function	0.18***	0.07	0.12	0.31	1.21	0.79	0.16*	0.09	0.20	0.47
Weak in Function	0.16***	0.06	- 0.12	0.24	0.94	1.19	0.21***	0.08	0.18	0.39
Good Design	0.17***	0.05	0.45***	0.18	0.33	0.63	0.03	0.07	0.13	0.40
Price Ratio	- 0.15***	0.05	0.80***	0.25	- 1.62*	1.11	- 0.51***	0.11	- 0.47	0.90
Word-of- Mouth	0.44***	0.04	0.36*	0.23	- 1.62*	0.93	0.60***	0.07	0.48	0.71

In sample is an unbalance panel that includes 400 individuals. The total number of observations is 8481
*p < .1, ** p < .05, *** p < .01
Made in Japan means product manufactured in Japan
COO in Japan means the country of origin of brand is Japan

Table 2: This table shows the results of parameters estimated from Probit model, finite mixture Probit model, and hierarchical Bayes Probit model.

		Constant	Made in China	Made in Japan	Made in US	COO in Japan	COO in US	Superiority in Function	Weak in Function	Superiority in Design	Price Ratio	Word-of-Mouth
Constant	Posterior Mean	4.72 ***	- 2.10 ***	- 2.05 ***	- 2.89 ***	0.26	- 2.65 ***	1.25	1.45 **	- 1.94 ***	- 4.27 ***	0.28
	Posterior STD	(1.18)	(0.87)	(0.91)	(1.08)	(0.89)	(1.03)	(0.88)	(0.83)	(0.85)	(0.96)	(0.80)
Gender	Posterior Mean	0.02	- 0.26	0.03	0.59	- 0.08	- 0.17	- 0.29	- 0.02	0.10	0.12	0.07
	Posterior STD	(0.46)	(0.32)	(0.48)	(0.63)	(0.39)	(0.43)	(0.38)	(0.34)	(0.36)	(0.44)	(0.34)
Age 21-30	Posterior Mean	- 0.55	0.85	1.42 ***	3.24 ***	- 0.95	0.04	- 0.59	- 0.18	0.93	- 0.12	- 0.71
	Posterior STD	(0.86)	(0.69)	(0.68)	(0.73)	(0.95)	(1.14)	(0.67)	(0.68)	(0.60)	(0.73)	(0.67)
Age 31-40	Posterior Mean	- 0.96	1.00	1.67 ***	2.76 ***	- 1.00	1.75 **	- 0.59	- 0.20	0.74	0.03	- 0.08
	Posterior STD	(0.79)	(0.70)	(0.79)	(0.80)	(0.83)	(1.01)	(0.59)	(0.61)	(0.54)	(0.74)	(0.59)
Age 41-50	Posterior Mean	- 0.95	1.27 **	1.67 ***	1.72 ***	- 0.89	2.12 ***	- 0.28	0.10	0.67	- 0.24	- 0.29
	Posterior STD	(0.78)	(0.68)	(0.66)	(0.77)	(0.89)	(0.96)	(0.60)	(0.59)	(0.58)	(0.72)	(0.58)
Age 51-60	Posterior Mean	- 1.00	1.00	1.81 ***	2.20 ***	- 0.93	2.06 ***	- 0.81	- 0.16	0.81	- 0.10	0.26
	Posterior STD	(0.84)	(0.70)	(0.75)	(0.79)	(0.85)	(0.99)	(0.64)	(0.62)	(0.56)	(0.73)	(0.58)
Age above 60	Posterior Mean	- 0.59	1.40 ***	1.02	1.59	- 0.15	2.59 ***	0.01	0.12	0.26	- 1.16 **	0.53
	Posterior STD	(0.93)	(0.62)	(0.92)	(0.90)	(0.96)	(1.04)	(0.72)	(0.73)	(0.66)	(0.67)	(0.69)
Frequency	Posterior Mean	- 0.03	0.00	0.02	0.02	- 0.02	0.01	0.00	0.01	0.01	0.01	- 0.01
	Posterior STD	(0.10)	(0.09)	(0.12)	(0.14)	(0.10)	(0.10)	(0.10)	(0.09)	(0.08)	(0.09)	(0.08)
Log_Amount	Posterior Mean	- 0.59 *	0.13	0.01	0.02	0.08	0.04	- 0.04	- 0.15	0.14	0.45	0.04
	Posterior STD	(0.36)	(0.27)	(0.30)	(0.32)	(0.25)	(0.29)	(0.28)	(0.26)	(0.26)	(0.30)	(0.25)

*$p < .1$, ** $p < .05$, *** $p < .01$
Log_amount means log average purchase amount

Table 3: This table shows the posterior mean and posterior standard deviation of Γ coefficients

Number of Product Recommended	In Sample Hit Rates (cumulative percentage) (1) Random Recommendation	(2) Probit Model	(3) Finite mixture Probit Model	(4) Hierarchical Bayes Probit	Out Sample Hit Rates (cumulative percentage) (1) Random Recommendation	(2) Probit Model	(3) Finite mixture Probit Model	(4) Hierarchical Bayes Probit
1	0.1128 %	0.2229 %	0.3325 %	0.4187 %	0.1207 %	0.2076 %	0.2398 %	0.2632 %
2	0.2242 %	0.3756 %	0.5406 %	0.6392 %	0.2414 %	0.3743 %	0.4561 %	0.4415 %
3	0.3371 %	0.5000 %	0.6761 %	0.7783 %	0.3621 %	0.5029 %	0.5819 %	0.5731 %
4	0.4472 %	0.6108 %	0.7685 %	0.8719 %	0.4828 %	0.6287 %	0.6754 %	0.7076 %
5	0.5553 %	0.7131 %	0.8349 %	0.9187 %	0.6013 %	0.7368 %	0.7661 %	0.8216 %
6	0.6527 %	0.7956 %	0.8805 %	0.9421 %	0.6993 %	0.8187 %	0.8509 %	0.8977 %
7	0.7304 %	0.8461 %	0.9089 %	0.9631 %	0.7710 %	0.8626 %	0.8918 %	0.9328 %
8	0.7902 %	0.8830 %	0.9335 %	0.9791 %	0.8194 %	0.8977 %	0.9240 %	0.9678 %
9	0.8369 %	0.9076 %	0.9483 %	0.9852 %	0.8772 %	0.9240 %	0.9591 %	0.9883 %
10	0.8695 %	0.9409 %	0.9557 %	0.9902 %	0.8793 %	0.9415 %	0.9678 %	0.9942 %

A random sample of 400 customers' transactions was selected for analysis. The last one purchase records of sampled customers were selected as hold out sample. There are 58 customer samples with only one transaction record. Accordingly, the hold out sample contains 342 actual transaction records of 342 customers. The in sample contains 811 actual transaction records of 400 customers

Table 4 is the comparison of cumulative percentage of hit rates. The hierarchical Bayes Probit model out performs the other models in either in sample and hold out sample prediction.

Appendix

To compare the performance of hit rates, we provide two basic solutions and two customized new product recommendation model for comparison.

Random Recommendation

The first one is random recommendation. It is assumed that no information regarding customer' preferences is available. If there are 10 products for choice, the hit rate for randomly recommending one product is 1/10.

Probit model

It is assumed no knowledge regarding individual's preference. However, the knowledge regarding the preference structure of aggregate market is available. Thus, their new product recommendations are based upon the same preference structure of their customers rather then customized new product recommendation. The Probit model is specified as follows:

$$y_{ij} = x'_{ij}\beta_i + \varepsilon_{ij} \qquad y_{ij} = 0,1, \quad i = 1,2,...,n, \quad j = 1,2,...,J_i$$

where ε_{ijm} follow normal distribution. Let y_{ij} to denote the choice made by individual *i in* J_i choice occasions, and x is a set of common product attributes.

Finite Mixture Probit Model

A finite mixture model that employs a finite set of mass points to capture heterogeneity has a history for the analysis of individual heterogeneity. It is assumed that individuals are implicitly sorted into a set of S classes, s=1, 2,…..S. In marketing application, these classes can be regarded as customer segments in the market. The following is a finite mixture Probit model for choice made by individual i (i=1, 2,…., N) observed in J_i choice situations, where x is a set of common product attributes. Let y_{ij} to denote the specific choice made by individual i in choice situation J_i, so that the model provides

$$\text{Prob}(y_{ij} = 1 \mid \text{class} = s) = \frac{\exp(\mathrm{x_{ij}}'\beta_s)}{1 + \exp(\mathrm{x_{ij}}'\beta_s)}$$

The individual specific parameter vector is $\hat{\beta}_i = \sum_{s=1}^{S} \hat{H}_{s|i}\hat{\beta}_s$ (Kamakura and Russell 1989). $\hat{H}_{s|i}$ is the individual i 's probabilities of being class s. This formula will be used to estimate individual preference toward product attributes to help us to predictive the purchase probability of any selected new or existing products.

Hierarchical Bayes Probit Model

The hierarchical Bayes approaches to modeling consumer heterogeneity have been conducted over a wide range of marketing problems (e.g., Allenby and Ginter 1995; Allenby, Arora, and Ginter 1998; Rossi and Allenby 2003). The model we will employ is the hierarchical Bayes Probit model. Let y_{ij} to denote the specific choice made by individual i in choice situation J_i,, x is a set of common product attributes,

$$y_{ij} = x'_{ij}\,\beta_i + \varepsilon_{ij} \qquad y_{ij} = 0,1, \quad i = 1, 2, \ldots, n, \quad j = 1, 2, \ldots, J_i$$

$$\beta_i = \Gamma \mathrm{z}_i + \zeta_i$$

where ε_{ij} follow normal distribution, n subjects or customers, and J_i choice occasions of subject *i*. β_i is a matrix of individualized preference coefficients, and Γ is a matrix of coefficients that relate β_i to the value of z_i, and z_i is a vector of covariates that account for observed heterogeneity. In this study, the covariate includes demographic variables (i.e., age, gender) and observed behavior variables in database (log average purchase amount and frequency). ζ_i is unobserved heterogeneity component, which is assumed to be multivariate normal distribution (Allenby and Ginter 1995). β_i will be used in this study to estimate individual preference toward product attributes to help us to predictive the purchase probability of any new products.